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A note on Chambers's "long memory and aggregation in macroeconomic time series"

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Abstract

Chambers (1998) explores the interaction between long memory and aggregation. For continuous-time processes, he takes the aliasing effect into account when studying temporal aggregation. For discrete-time processes, however, he seems to fail to do so. This note gives the spectral density function of temporally aggregated long memory discrete-time processes in light of the aliasing effect. The results are different from those in Chambers (1998) and are supported by a small simulation exercise. As a result, the order of aggregation may not be invariant to temporal aggregation, specifically if d is negative and the aggregation is of the stock type.

JEL classification: C14, C22, C43

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1 - Introduction

Chambers (1998) investigates the spectral density function of stock and flow aggregated long memory processes, as well as continuous-time long memory processes observed at discrete-time intervals and cross-sectionally aggregated long memory processes. For the temporal aggregation of discrete-time processes, however, he does not take into account the aliasing effect as he does in the case of the continuous-time processes.

This note derives the spectral density function of aggregated stock and flow long memory processes in light of the Aliasing Theorem. The resulting formulae are different from those in Chambers (1998), and a simulation study brings evidence in my favor. The Aliasing Theorem is adapted to the case in which a discrete-time process is observed at a slower sampling rate. One of the main results of Chambers (1998), namely that the integration order is invariant to temporal aggregation, still holds in most cases, the exception being aggregation of stock processes with a negative order of integration. On the other hand, the second testable implication of the theory (Chambers 1998, Section 2.5) may be seriously impaired by the bias incurred by temporal aggregation in stock aggregates, as reported by Souza and Smith (2002). The next section contains my specific points, while Section 3 provides some discussion on the results.

2 – Accounting of the aliasing effect

I modify slightly the notation used by Chambers (1998), particularly in that I define the properties in the time unit of the original sampling frequency, whereas he uses the time unit of the aggregates. I use n as the level of aggregation, instead of p, so as to avoid confusion with the AR order p. Also, I opt for saving notation in some equations.

Definition 1: The temporally aggregated variable Y_t is observed as follows:

1a) If X_t is a stock variable, then $Y_t = X_{nt}$, $t = 1, \ldots, T$.

1b) If X_t is a flow variable, then $Y_t = \sum_{j=0}^{n-1} X_{nt-j} = \sum_{j=0}^{n-1} B^j X_{nt}$, $t = 1, \ldots, T$.

The difference between Definition 1a) and 1b) is that a moving average filter $(1 + B + \ldots + B^{n-1})$ is applied to X_t in the case of a flow variable before skip-sampling, while the stock variable is simply "skip-sampled".

2.1 – Results from Theorem 1 of Chambers

Chambers (1998) works with the following frequency-domain definition of long memory. X_t is a long memory process if its spectral density function satisfies

(1) $$f(\lambda) \sim c|\lambda|^{-2d} \text{ as } \lambda \to 0,$$

for some $0 < c < \infty$ and $-0.5 < d < 0.5$, where λ is the frequency. This definition implies that $f(\lambda)$ has a zero or a pole at $\lambda = 0$ respectively if $d < 0$ or $d > 0$. Autoregressive fractionally integrated moving average (ARFIMA) models, introduced by Hosking (1981) and Granger and Joyeux (1980), are able to reproduce the behavior described by (1). X_t follows an ARFIMA(p,d,q) model if $\Phi(B)(1-B)^d X_t = \Theta(B)\varepsilon_t$, where ε_t is a mean-zero, constant variance (σ_ε^2) white noise process, B is the backward shift operator such that $BX_t = X_{t-1}$, and $\Phi(B)=1-\phi_1B-\ldots-\phi_pB^p$ and $\Theta(B)=1+\theta_1B+\ldots+\theta_qB^q$ are the autoregressive and moving-average polynomials, respectively. If the roots of $\Phi(B)$ are outside the unit circle, the process is stationary and if the roots of $\Theta(B)$ are outside the unity circle the process is invertible. The spectral density function of stationary ARFIMA processes is given by:

(2) $$f(\lambda) = \frac{\sigma_\varepsilon^2}{2\pi}\left|1-e^{-i\lambda}\right|^{-2d}\frac{\left|\Theta(e^{-i\lambda})\right|^2}{\left|\Phi(e^{-i\lambda})\right|^2}, \qquad -\pi < \lambda \le \pi,$$

where $i^2 = -1$.

With these results, Chambers argues that, if X_t has the Wold representation $(1-B)^{(\delta+d)}X_t = \sum_{h=0}^{\infty}\rho_h\varepsilon_{t-h} = \rho(B)\varepsilon_t$, where $\rho_0 = 1$, $\sum_{h=1}^{\infty}|\rho_h| < \infty$, ε_t is a white noise sequence with variance σ_ε^2, $-0.5 < d < 0.5$, and δ is an integer number; then the aggregated process Y_t has the following spectral density:

(3) $$f_Y(\lambda) = \frac{\sigma_\varepsilon^2}{2\pi}\left|1-e^{-i\lambda/n}\right|^{-2(\delta+d)}\left|\rho(e^{-i\lambda/n})\right|^2, \qquad -\pi < \lambda \le \pi,$$

if X_t is a stock variable; and

(4) $$f_Y(\lambda) = \frac{\sigma_\varepsilon^2}{2\pi}\left|1-e^{-i\lambda/n}\right|^{-2(\delta+d)}\left|\rho(e^{-i\lambda/n})\right|^2\left|\sum_{k=0}^{n-1}e^{-ik\lambda/n}\right|^2, \qquad -\pi < \lambda \le \pi,$$

if X_t is a flow variable. I shall point out here that a spectral density is well defined only if the process is second-order stationary, which is not taken into account in (3-4), as δ is allowed to take on positive integer values, characterizing non-stationarity. However, this is a minor comment in this note, the major one referring to the aliasing effect explained next.

2.2 – Aliasing effect

Temporal aggregation as defined includes at some part the act of skip-sampling. This causes the aliasing phenomenon, well known in the signal processing literature for continuous-time processes observed at discrete-time intervals. The literature seems to give little heed, however, to the fact that the same causes for the aliasing to appear when observing a continuous process at discrete-time are also present in the act of skip-sampling. In fact, a number of signal processing and time series books (e.g. Koopmans 1974, Bloomfield 1976, Priestley 1981, Oppenheim and Schafer 1989, Hamilton 1994) explain the aliasing effect only as a phenomenon which arises when observing continuous-time processes at discrete intervals. However, the explanation of this phenomenon and the derivation of its effects when observing a discrete process at a lower sampling rate are almost identical. The difference lies in that the spectral density function of discrete-time processes is defined only over the range $(-\pi, \pi]$ while that of continuous-time processes is defined over the real line $\Re$.

An intuitive explanation of the aliasing phenomenon occurring in discrete processes observed at a lower sampling frequency is the following. When the sampling frequency is lower than that of the underlying process by a factor n, a component with frequency ω in the original process will have (nominal) frequency $\lambda = n\omega$ in the newly sampled series, possibly falling outside $(-\pi, \pi]$. Alternatively, the frequency interval $(-\pi, \pi]$ for λ in the spectrum of the aggregated process is equivalent to $(-\pi/n, \pi/n]$ for ω in the original process. Clearly some frequencies of the original process will not be directly observed in the aggregated process (and therefore will not appear in its spectrum), for they will complete more than an entire cycle between two subsequent observations, since their respective periods are smaller than the sampling period. Instead, components with these frequencies will have an apparent (lower) frequency in the aggregated process, different from the "real" frequency. All frequencies under the same apparent frequency will be observed together. This is, loosely speaking, the aliasing effect and is equivalent to folding the spectrum n times into the interval $(-\pi/n, \pi/n]$. The aliasing effect arising from aggregating discrete-time stock processes is given as part of the following theorem:

Theorem 1*: Let X_t be a covariance stationary discrete-time process with spectral density function $f_x(\omega)$ and Y_t the corresponding aggregated process. The spectral density function of Y_t, $f_y(\lambda)$, is given by:*

1a) If n is an odd number:

(5)
$$f_y(\lambda) = \frac{1}{n} \sum_{j=-\frac{n-1}{2}}^{\frac{n-1}{2}} g\left(n, \frac{\lambda}{n} + \frac{2j\pi}{n}\right) f_x\left(\frac{\lambda}{n} + \frac{2j\pi}{n}\right), \qquad -\pi < \lambda \leq \pi;$$

1b) If n is an even number:

$$
(6) \qquad f_y(\lambda)=\begin{cases}\dfrac{1}{n}\displaystyle\sum_{j=1-\frac{n}{2}}^{\frac{n}{2}} g\left(n,\dfrac{\lambda}{n}+\dfrac{2j\pi}{n}\right)f_x\left(\dfrac{\lambda}{n}+\dfrac{2j\pi}{n}\right), & -\pi<\lambda\le 0\\[2ex] \dfrac{1}{n}\displaystyle\sum_{j=-\frac{n}{2}}^{\frac{n}{2}-1} g\left(n,\dfrac{\lambda}{n}+\dfrac{2j\pi}{n}\right)f_x\left(\dfrac{\lambda}{n}+\dfrac{2j\pi}{n}\right), & 0<\lambda\le\pi\end{cases},
$$

where $g(n,\omega) = 1$ if the aggregation is of the stock type and $g(n,\omega) =$ $2\pi n F_n(\omega)=\lim_{\theta\to\omega}\dfrac{sin^2(n\theta/2)}{sin^2(\theta/2)}$ if the aggregation is of the flow type.

The pure aliasing effect appears in the aggregation of stock variables, when $g(n,\omega) = 1$, but it also appears in the aggregation of flow variables, mixed with other effects introduced by the moving average filter $(1 + B + \ldots + B^{n-1})$. The function $F_n(\omega)$ is the Fejer kernel (details in Priestley, 1981) and is periodic with period equal to 2π. For ω restricted to the interval $(-\pi, \pi]$, it has the highest peak at the frequency zero (far higher than the subsidiary peaks) and zeros at frequencies that are nonzero multiples of $2\pi/n$ (Nyquist frequency) as shown in Figure 1 for $n = 6$. Figure 1 illustrates clearly that after applying a moving average filter $(1+B+\ldots+B^{n-1})$, the low frequencies predominate. Furthermore, the Fejer kernel first derivative is zero at all (zero and nonzero) multiples of the Nyquist frequency and the nonzero multiples will be folded into the frequency zero after a further skip-sampling, so that the aliasing effect is offset in the aggregation of the flow type at lower frequencies.

The main part of the proof of Theorem 1 is adapted from the proof of the Aliasing Theorem for continuous-time processes observed at discrete-time intervals, easily found in the Spectral Analysis books, e.g. Priestley (1981) and Oppenheim and Schafer (1989).

2.3 – Spectrum of aggregated long memory processes

Having stated Theorem 1, it is straightforward to calculate the spectrum of temporal aggregates of fractionally integrated processes using equation (2).

***Corollary 1**: Let X_t have the Wold representation $X_t=(1-B)^{-d}\rho(B)\varepsilon_t$ where $\rho_0 = 1$, $\sum_{h=1}^{\infty}|\rho_h|<\infty$, ε_t is a white noise sequence with variance σ_ε^2, $-0.5 < d < 0.5$. Then, for $-\pi < \lambda \le \pi$, the spectrum of the aggregated variable Y_t is given by:*

***1a)** If X_t is a stock variable:*

(7) $$f_y(\lambda) = \frac{\sigma_\varepsilon^2}{2n\pi}\sum_{j=0}^{n-1}\left[\left|1-e^{-i(\lambda+j2\pi)/n}\right|^{-2d}\left|\rho(e^{-i(\lambda+j2\pi)/n})\right|^2\right];$$

***1b)** If X_t is a flow variable:*

(8) $$f_y(\lambda) = \sigma_\varepsilon^2\sum_{j=0}^{n-1}\left[\left|1-e^{-i(\lambda+j2\pi)/n}\right|^{-2d}\left|\rho(e^{-i(\lambda+j2\pi)/n})\right|^2 F_n((\lambda+j2\pi)/n)\right].$$

The change in the summation indices is undertaken to unify the results for even and odd values of *n*, and does not affect the results because of the periodicity displayed by the exponential of imaginary numbers.

2.4 – Simulation

In this subsection a small simulation is carried out to compare the spectral density function given in Corollary 1 for aggregated long memory processes with that given by Theorem 1 of Chambers (1998) as displayed in equations (3-4). Figure 2 shows the spectral function derived in this note for aggregated stock ARFIMA processes and the one derived in Chambers (1998), together with the periodogram ordinates averaged across 100 realizations of the process. The X axis shows the indices $j = 1, 2, \ldots, \lfloor T/2 \rfloor$ representing the Fourier frequencies $j2\pi/T$. Figure 3 does the same as Figure 2, but for flow processes. The processes are aggregated from ARFIMA(0,0.3,0), with $n = 3$; ARFIMA(1,0.3,0) with $\phi = 0.8$ and $n = 4$; ARFIMA(0,0.3,1) with $\theta = -0.8$ and $n = 4$; ARFIMA(1,0.3,1) with $\phi = -0.4$, $\theta = -0.8$ and $n = 3$. The aggregated series length is 512 observations and the error variance is taken as $\sigma_\varepsilon^2 = 1$.

As we can see for both stock and flow aggregated ARFIMA processes the averaged periodogram ordinates (dots) are scattered around the solid line, which represents the formulae (7-8) derived in this note. The formulae derived in Chambers (1998) and displayed in (3-4), represented by a dashed line, yields values somewhat different from the observed in the simulation experiment.

3 – Discussion

This note aims at disputing some of the results derived in Chambers (1998), specifically the spectrum of temporal aggregates of discrete-time long memory processes. The main point is that the aliasing effect was not taken into account. I provide here the corresponding spectrum in light of the aliasing effect. A small simulation provides evidence in my favor.

As a result, two of the implications of Chambers (1998) results must be reviewed. First, that the integration order remains constant after temporal aggregation. This is true for the aggregation of flow variables, as the moving average filter ($1 + B + \ldots + B^{n-1}$) assigns weights equal to zero to the frequencies which will alias right onto the frequency zero and very small for those aliasing on its vicinity. For aggregation of stock variables, if *d* is positive, the unbounded energy in the spectrum for low frequencies in the original process dominates the energy coming from aliases of these low frequencies in the aggregated process (if this energy is bounded), and a condition similar to (1) still holds with same parameter *d*. However, if aggregating a stock variable with negative *d*, the condition (1), that implies a zero in the frequency zero, will surely be destroyed, unless in the very unlikely case where the spectrum in the frequencies which will alias on the frequency zero is zero. A curious note is that, if long memory is defined in the time domain as a hyperbolical decay of the autocorrelations,

(9) $$\rho_k \sim c|k|^{2d-1} \text{ as k} \rightarrow \infty,$$

temporal aggregation of either type (stock or flow) is not able to destroy this property, and not even to change the integration order *d*. This result, however, is of lesser practical importance because a negative *d* is rarely observed empirically, but arises frequently from overdifferencing a process. As practitioners usually aggregate series before differencing them and not otherwise, it is unlikely that a (stock) process with negative *d* will be aggregated.

The second implication to be reviewed is the second testable hypothesis of Chambers (1998, Section 2.5). He argues that the order of integration should be the same when estimated from different frequencies of the data. This is true for flow variables but not for stock ones. Even though the aggregation of stock variables retains the spectrum behavior in a small neighborhood of zero if $d > 0$, the aggregation of flow variables do it in a far wider neighborhood, irrespective of the sign of *d*. These different frequency-domain behaviors of stock and flow variables will distinctly affect the (semiparametric) estimation of aggregated fractionally differenced processes based on the low-frequency periodogram ordinates. If the process is a flow variable, less bias is likely to be induced by aggregation, while if it is a stock variable, it is likely that aggregation will incur some bias. In particular, if $d < 0$, the aggregation of stock fractionally integrated processes will destroy condition (1). However, for positive *d*, when the sample size increases the bias tends to disappear as a narrower band of frequencies is used for estimation. These conjectures are largely consistent with Monte Carlo results from Souza and Smith (2002, 2003).

Appendix – Proof of Theorem 1

The spectrum of a covariance stationary discrete-time process X_t is defined by:

$$f_x(\omega) = \frac{1}{2\pi}\sum_{k=-\infty}^{\infty}\gamma_k^x e^{-ik\omega}\,, \qquad -\pi < \omega \le \pi \qquad (A1)$$

where γ_k^x is the k-th order autocovariance of X_t. As the autocovariance function of real valued processes is an even function, (A1) reduces to:

$$f_x(\omega) = \frac{1}{2\pi}\sum_{k=-\infty}^{\infty}\gamma_k^x \cos k\omega\,, \qquad -\pi < \omega \le \pi. \qquad (A2)$$

The spectrum $f_x(\omega)$ is then defined as a Fourier cosine series whose coefficients are the autocovariances of X_t. As $\cos k\omega$, k = 0, 1, 2, ..., is a complete orthogonal set over the interval (–π, π] for even functions (and the spectral density is an even function) the relation given by (A2) is equivalent to:

$$\gamma_k^x = \int_{-\pi}^{\pi} f_x(\omega)\cos k\omega\, d\omega = \int_{-\pi}^{\pi}\cos k\omega\, dF_x(\omega), \qquad k = 0, \pm 1, \pm 2, \ldots \qquad (A3)$$

where $F_x(\omega)$ is the spectral distribution function of X_t. Consider first the aggregation of stock variables. The autocovariances of $Y_t = X_{nt}$ are given thus by:

$$\gamma_k^y = \gamma_{nk}^x = \int_{-\pi}^{\pi} f_x(\omega)\cos nk\omega\, d\omega = \int_{-\pi}^{\pi}\cos nk\omega\, dF_x(\omega), \qquad k = 0, \pm 1, \pm 2, \ldots \qquad (A4)$$

First take the simpler case where n is an odd number. The integral in (A4) can be split into:

$$\gamma_k^y = \sum_{j=-\frac{n-1}{2}}^{\frac{n-1}{2}} \int_{(2j-1)\pi/n}^{(2j+1)\pi/n}\cos nk\omega\, dF_x(\omega) = \sum_{j=-\frac{n-1}{2}}^{\frac{n-1}{2}} \int_{-\pi/n}^{\pi/n}\cos(nk\omega + 2jk\pi)\, dF_x(\omega + 2j\pi/n) \quad (A5)$$

Since cos(a + 2jπ) = cos(a), where j is an integer number, *(A5)* rewrites to:

$$\gamma_k^y = \sum_{j=-\frac{n-1}{2}}^{\frac{n-1}{2}} \int_{-\pi/n}^{\pi/n}\cos(nk\omega)\, dF_x(\omega + 2j\pi/n) \qquad (A6)$$

Making $\lambda = n\omega$ where λ is the frequency measured in the time unit of Y_t, we have:

$$\gamma_k^y = \sum_{j=-\frac{n-1}{2}}^{\frac{n-1}{2}} \int_{-\pi}^{\pi}\cos(k\lambda)\frac{1}{n}\, dF_x(\lambda/n + 2j\pi/n) \qquad (A7)$$

However, by (A3) we can write the k-th order autovariance of Y_t as:

$$\gamma_k^y = \int_{-\pi}^{\pi} f_y(\lambda)\cos k\lambda\, d\lambda = \int_{-\pi}^{\pi}\cos k\lambda\, dF_y(\lambda), \qquad k = 0, \pm 1, \pm 2, \ldots \qquad (A8)$$

The fact that cos $k\lambda$, k = 0, 1, 2, ..., is a complete orthogonal set over the interval (–π, π] for even functions, together with (A7) and (A8) imply (5) with $g(n,\omega) = 1$.

Now if n is an even number (A5) rewrites to:

$$\gamma_k^y = \sum_{j=1-\frac{n}{2}}^{\frac{n}{2}} \int_{-\pi/n}^{0} \cos(nk\omega + 2jk\pi)\, dF_x(\omega + 2j\pi/n) + \\ + \sum_{j=-\frac{n}{2}}^{\frac{n}{2}-1} \int_{0}^{\pi/n} \cos(nk\omega + 2jk\pi)\, dF_x(\omega + 2j\pi/n) \qquad (A9)$$

and the rest of the proof (for stock processes) follows as in the case n is odd.

Now consider the aggregation of flow variables. Let $Z_t = \sum_{j=0}^{n-1} B^j X_t$ be the overlapping aggregated process of X_t. The moving average representation of $(1 + B + \ldots + B^{n-1})$ straightforwardly gives the following relationship between the spectra of Z_t and X_t:

$f_z(\omega) = f_x(\omega)\left|\sum_{k=0}^{n-1} e^{-ik\omega}\right|^2$, $-\pi < \omega \le \pi$. The multiplicative term $\left|\sum_{k=0}^{n-1} e^{-ik\omega}\right|^2$ is equivalent to

$\lim_{\theta\to\omega} \frac{sin^2(n\theta/2)}{sin^2(\theta/2)} = 2\pi n.F_n(\omega)$. This latter result can be easily verified (see, for example, Bloomfield 1976, p. 51). Now, the aggregated process Y_t is obtained from Z_t through an aggregation of the stock type, and the relationship between the spectra of Y_t and X_t is that given in Theorem 1. The proof is complete.

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Figure 1: The Fejer kernel for n = 6, restricted to (-π, π]

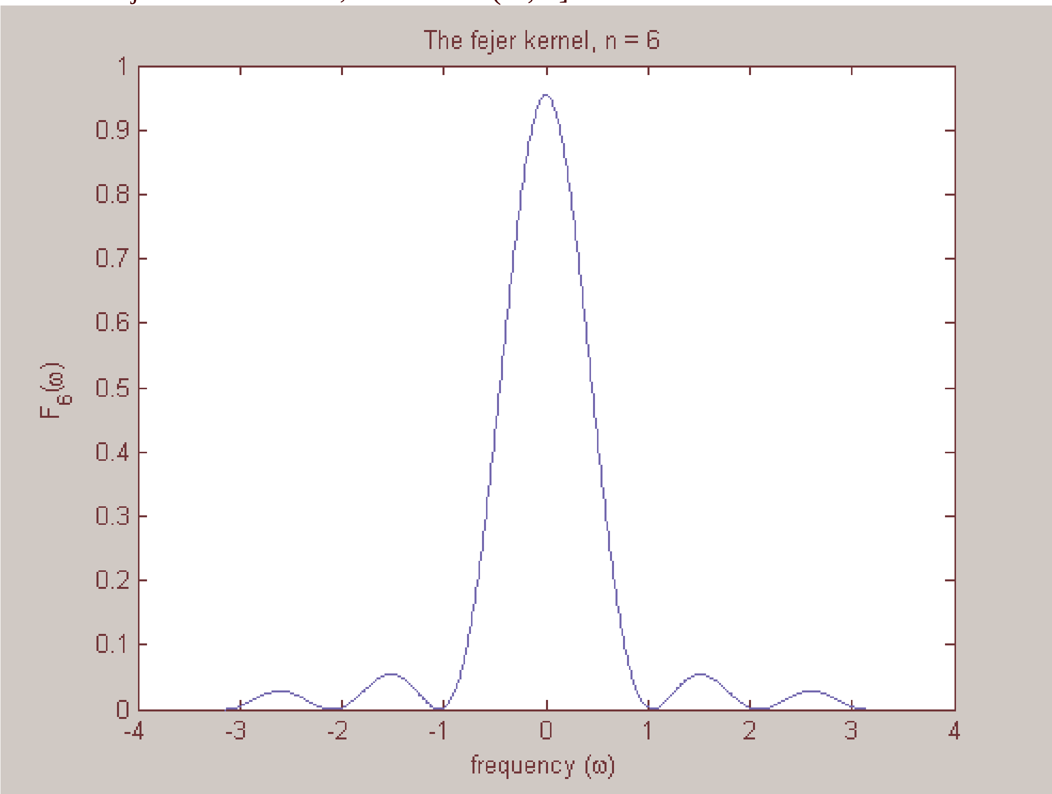


Figure 2: Chambers's (1998) and this note's theoretical spectral functions for aggregated stock ARFIMA processes, respectively the dashed and the continuous lines. The dots correspond to periodogram ordinates averaged across 100 realizations of the processes.

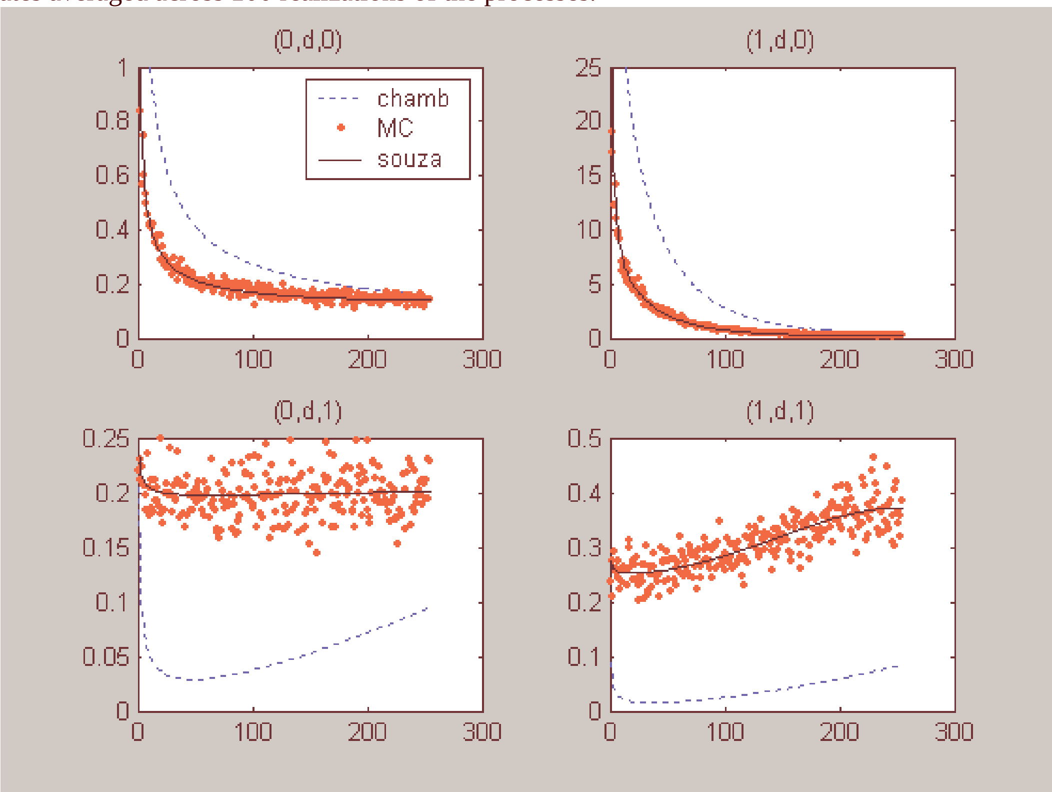
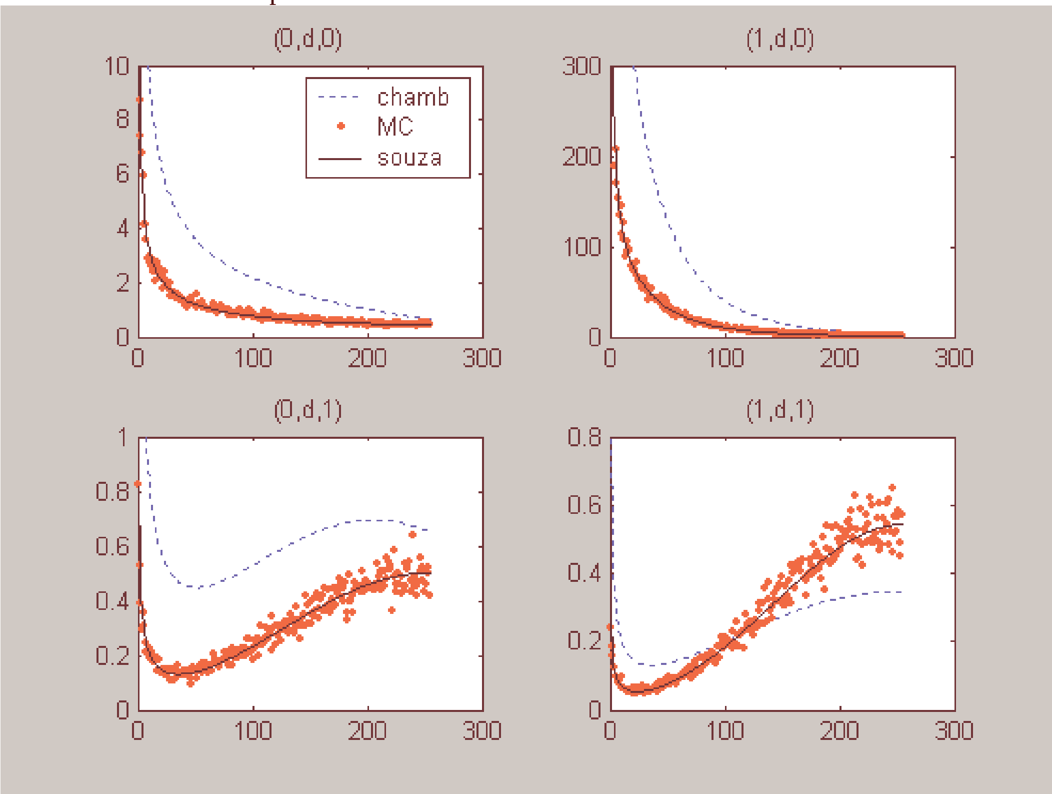


Figure 3: Chambers's (1998) and this note's theoretical spectral functions for aggregated flow ARFIMA processes, respectively the dashed and the continuous lines. The dots correspond to periodogram averaged across 100 realizations of the processes.



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